# CPSC 330
# Applied Machine Learning

## Lecture 6: `sklearn ColumnTransformer` and Text Features

UBC 2022-23

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## Imports

In [1]:
```
import os
import sys

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from IPython.display import HTML

sys.path.append("../code/.")
from plotting_functions import *
from utils import *

pd.set_option("display.max_colwidth", 200)

from sklearn.compose import ColumnTransformer, make_column_transformer
from sklearn.dummy import DummyClassifier, DummyRegressor
from sklearn.impute import SimpleImputer
from sklearn.model_selection import cross_val_score, cross_validate, tr
from sklearn.neighbors import KNeighborsClassifier, KNeighborsRegressor
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, Standa
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
```

# Learning outcomes

From this lecture, you will be able to

- use `ColumnTransformer` to build all our transformations together into one object and use it with `sklearn` pipelines;
- define `ColumnTransformer` where transformers contain more than one steps;
- explain `handle_unknown="ignore"` hyperparameter of `scikit-learn` 's `OneHotEncoder` ;
- explain `drop="if_binary"` argument of `OneHotEncoder` ;
- identify when it's appropriate to apply ordinal encoding vs one-hot encoding;
- explain strategies to deal with categorical variables with too many categories;
- explain why text data needs a different treatment than categorical variables;
- use `scikit-learn` 's `CountVectorizer` to encode text data;
- explain different hyperparameters of `CountVectorizer` .

# sklearn's `ColumnTransformer` (https://scikit-learn.org/stable/modules/generated/sklearn.compose.Colur

- In most applications, some features are categorical, some are continuous, some are binary, and some are ordinal.
- When we want to develop supervised machine learning pipelines on real-world datasets, very often we want to apply different transformation on different columns.
- Enter `sklearn` 's `ColumnTransformer` !!

- Let's look at a toy example:

In [2]:
```
df = pd.read_csv("../data/quiz2-grade-toy-col-transformer.csv")
df
```

Out[2]:

| | enjoy_course | ml_experience | major | class_attendance | university_years | lab1 | lab2 | lab3 | l |
|---|---|---|---|---|---|---|---|---|---|
| **0** | yes | 1 | Computer Science | Excellent | 3 | 92 | 93.0 | 84 | |
| **1** | yes | 1 | Mechanical Engineering | Average | 2 | 94 | 90.0 | 80 | |
| **2** | yes | 0 | Mathematics | Poor | 3 | 78 | 85.0 | 83 | |
| **3** | no | 0 | Mathematics | Excellent | 3 | 91 | NaN | 92 | |
| **4** | yes | 0 | Psychology | Good | 4 | 77 | 83.0 | 90 | |
| **5** | no | 1 | Economics | Good | 5 | 70 | 73.0 | 68 | |
| **6** | yes | 1 | Computer Science | Excellent | 4 | 80 | 88.0 | 89 | |
| **7** | no | 0 | Mechanical Engineering | Poor | 3 | 95 | 93.0 | 69 | |
| **8** | no | 0 | Linguistics | Average | 2 | 97 | 90.0 | 94 | |
| **9** | yes | 1 | Mathematics | Average | 4 | 95 | 82.0 | 94 | |
| **10** | yes | 0 | Psychology | Good | 3 | 98 | 86.0 | 95 | |
| **11** | yes | 1 | Physics | Average | 1 | 95 | 88.0 | 93 | |
| **12** | yes | 1 | Physics | Excellent | 2 | 98 | 96.0 | 96 | |
| **13** | yes | 0 | Mechanical Engineering | Excellent | 4 | 95 | 94.0 | 96 | |
| **14** | no | 0 | Mathematics | Poor | 3 | 95 | 90.0 | 93 | |
| **15** | no | 1 | Computer Science | Good | 3 | 92 | 85.0 | 67 | |
| **16** | yes | 0 | Computer Science | Average | 5 | 75 | 91.0 | 93 | |
| **17** | yes | 1 | Economics | Average | 3 | 86 | 89.0 | 65 | |
| **18** | no | 1 | Biology | Good | 2 | 91 | NaN | 90 | |
| **19** | no | 0 | Psychology | Poor | 2 | 77 | 94.0 | 87 | |
| **20** | yes | 1 | Linguistics | Excellent | 4 | 96 | 92.0 | 92 | |

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21 entries, 0 to 20
Data columns (total 11 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   enjoy_course      21 non-null     object 
 1   ml_experience     21 non-null     int64  
 2   major             21 non-null     object 
 3   class_attendance  21 non-null     object 
 4   university_years  21 non-null     int64  
 5   lab1              21 non-null     int64  
 6   lab2              19 non-null     float64
 7   lab3              21 non-null     int64  
 8   lab4              21 non-null     int64  
 9   quiz1             21 non-null     int64  
 10  quiz2             21 non-null     object 
dtypes: float64(1), int64(6), object(4)
memory usage: 1.9+ KB
```

## Transformations on the toy data

In [4]:
```
df.head()
```

Out[4]:

| | enjoy_course | ml_experience | major | class_attendance | university_years | lab1 | lab2 | lab3 | la |
|---|---|---|---|---|---|---|---|---|---|
| **0** | yes | 1 | Computer Science | Excellent | 3 | 92 | 93.0 | 84 | |
| **1** | yes | 1 | Mechanical Engineering | Average | 2 | 94 | 90.0 | 80 | |
| **2** | yes | 0 | Mathematics | Poor | 3 | 78 | 85.0 | 83 | |
| **3** | no | 0 | Mathematics | Excellent | 3 | 91 | NaN | 92 | |
| **4** | yes | 0 | Psychology | Good | 4 | 77 | 83.0 | 90 | |

- Scaling on numeric features
- One-hot encoding on the categorical feature `major` and binary feature `enjoy_class`
- Ordinal encoding on the ordinal feature `class_attendance`
- Imputation on the `lab2` feature
- None on the `ml_experience` feature

## `ColumnTransformer` example

### Data

In [5]:
```python
X = df.drop(columns=["quiz2"])
y = df["quiz2"]
X.columns
```

Out[5]:
```
Index(['enjoy_course', 'ml_experience', 'major', 'class_attendance',
       'university_years', 'lab1', 'lab2', 'lab3', 'lab4', 'quiz1'],
      dtype='object')
```

### Identify the transformations we want to apply

In [9]:
```python
X.head()
```

Out[9]:

| | enjoy_course | ml_experience | major | class_attendance | university_years | lab1 | lab2 | lab3 | la |
|---|---|---|---|---|---|---|---|---|---|
| **0** | yes | 1 | Computer Science | Excellent | 3 | 92 | 93.0 | 84 | |
| **1** | yes | 1 | Mechanical Engineering | Average | 2 | 94 | 90.0 | 80 | |
| **2** | yes | 0 | Mathematics | Poor | 3 | 78 | 85.0 | 83 | |
| **3** | no | 0 | Mathematics | Excellent | 3 | 91 | NaN | 92 | |
| **4** | yes | 0 | Psychology | Good | 4 | 77 | 83.0 | 90 | |

In [10]:
```python
numeric_feats = ["university_years", "lab1", "lab3", "lab4", "quiz1"]
categorical_feats = ["major"]  # apply one-hot encoding
passthrough_feats = ["ml_experience"]  # do not apply any transformatio
drop_feats = [
    "lab2",
    "class_attendance",
    "enjoy_course",
]  # do not include these features in modeling
```

For simplicity, let's only focus on scaling and one-hot encoding first.

### Create a column transformer

- Each transformation is specified by a name, a transformer object, and the columns this transformer should be applied to.

In [7]:
```python
from sklearn.compose import ColumnTransformer
```

In [11]:
```
ct = ColumnTransformer(
    [
        ("scaling", StandardScaler(), numeric_feats),
        ("onehot", OneHotEncoder(sparse=False), categorical_feats),
    ]
)
```

### Convenient `make_column_transformer` syntax

- Similar to `make_pipeline` syntax, there is convenient `make_column_transformer` syntax.
- The syntax automatically names each step based on its class.
- We'll be mostly using this syntax.

In [13]:
```
from sklearn.compose import make_column_transformer

ct = make_column_transformer(
    (StandardScaler(), numeric_feats),  # scaling on numeric features
    (OneHotEncoder(), categorical_feats),  # OHE on categorical feature
    ("passthrough", passthrough_feats),  # no transformations on the bi
    ("drop", drop_feats),  # drop the drop features
)
```

In [14]:
```
ct
```

Out[14]:
```
ColumnTransformer(transformers=[('standardscaler', StandardScaler(),
                                 ['university_years', 'lab1', 'lab3', 'la
b4',
                                  'quiz1']),
                                ('onehotencoder', OneHotEncoder(), ['majo
r']),
                                ('passthrough', 'passthrough',
                                 ['ml_experience']),
                                ('drop', 'drop',
                                 ['lab2', 'class_attendance', 'enjoy_cour
se'])])
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**
**On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

In [15]:
```
transformed = ct.fit_transform(X)
```

- When we `fit_transform`, each transformer is applied to the specified columns and the result of the transformations are concatenated horizontally.
- A big advantage here is that we build all our transformations together into one object, and that way we're sure we do the same operations to all splits of the data.
- Otherwise we might, for example, do the OHE on both train and test but forget to scale the test data.

#### Let's examine the transformed data

In [16]:
```
type(transformed[:2])
```

Out[16]:
```
numpy.ndarray
```

In [17]:

```
transformed
```

Out[17]:
```
array([[-0.09345386,  0.3589134 , -0.21733442,  0.36269995,  0.84002795,
         0.        ,  1.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  0.        ,  1.        ],
       [-1.07471942,  0.59082668, -0.61420598, -0.85597188,  0.71219761,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         1.        ,  0.        ,  0.        ,  1.        ],
       [-0.09345386, -1.26447953, -0.31655231, -1.31297381, -0.69393613,
         0.        ,  0.        ,  0.        ,  0.        ,  1.        ,
         0.        ,  0.        ,  0.        ,  0.        ],
       [-0.09345386,  0.24295676,  0.57640869,  0.36269995,  0.45653693,
         0.        ,  0.        ,  0.        ,  0.        ,  1.        ,
         0.        ,  0.        ,  0.        ,  0.        ],
       [ 0.8878117 , -1.38043616,  0.37797291,  0.51503393, -0.05478443,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  1.        ,  0.        ],
       [ 1.86907725, -2.19213263, -1.80482065, -2.22697768, -1.84440919,
         0.        ,  0.        ,  1.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  0.        ,  1.        ],
       [ 0.8878117 , -1.03256625,  0.27875502, -0.09430199,  0.71219761,
         0.        ,  1.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  0.        ,  1.        ],
       [-0.09345386,  0.70678332, -1.70560276, -1.46530779, -1.33308783,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         1.        ,  0.        ,  0.        ,  0.        ],
       [-1.07471942,  0.93869659,  0.77484447, -1.00830586, -0.69393613,
         0.        ,  0.        ,  0.        ,  1.        ,  0.        ,
         0.        ,  0.        ,  0.        ,  0.        ],
       [ 0.8878117 ,  0.70678332,  0.77484447,  0.81970188, -0.05478443,
         0.        ,  0.        ,  0.        ,  0.        ,  1.        ,
         0.        ,  0.        ,  0.        ,  1.        ],
       [-0.09345386,  1.05465323,  0.87406235,  0.97203586, -0.94959681,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  1.        ,  0.        ],
       [-2.05598498,  0.70678332,  0.67562658,  0.51503393, -0.05478443,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  1.        ,  0.        ,  1.        ],
       [-1.07471942,  1.05465323,  0.97328024,  1.58137177,  1.86267067,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  1.        ,  0.        ,  1.        ],
       [ 0.8878117 ,  0.70678332,  0.97328024,  0.97203586,  1.86267067,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         1.        ,  0.        ,  0.        ,  0.        ],
       [-0.09345386,  0.70678332,  0.67562658,  0.97203586, -1.97223953,
         0.        ,  0.        ,  0.        ,  0.        ,  1.        ,
         0.        ,  0.        ,  0.        ,  0.        ],
       [-0.09345386,  0.3589134 , -1.90403853,  0.81970188,  0.84002795,
         0.        ,  1.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  0.        ,  1.        ],
       [ 1.86907725, -1.61234944,  0.67562658, -0.39896994, -0.05478443,
         0.        ,  1.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  0.        ,  0.        ],
       [-0.09345386, -0.33682642, -2.10247431, -0.39896994,  0.20087625,
         0.        ,  0.        ,  1.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  0.        ,  1.        ],
       [-1.07471942,  0.24295676,  0.37797291, -0.09430199, -0.43827545,
         1.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  0.        ,  1.        ],
```

```
       [-1.07471942, -1.38043616,  0.08031924, -1.16063983,  0.45653693,
         0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  1.        ,  0.        ],
       [ 0.8878117 ,  0.82273995,  0.57640869,  1.12436984,  0.20087625,
         0.        ,  0.        ,  0.        ,  1.        ,  0.        ,
         0.        ,  0.        ,  0.        ,  1.        ]])
```

```
Note that the returned object is not a dataframe. So there are no c
olumn names.
```

#### Viewing the transformed data as a dataframe

- How can we view our transformed data as a dataframe?
- We are adding more columns.
- So the original columns won't directly map to the transformed data.
- Let's create column names for the transformed data.

In [18]:
```
column_names = (
    numeric_feats
    + ct.named_transformers_["onehotencoder"].get_feature_names_out().t
    + passthrough_feats
)
column_names
```

Out[18]:
```
['university_years',
 'lab1',
 'lab3',
 'lab4',
 'quiz1',
 'major_Biology',
 'major_Computer Science',
 'major_Economics',
 'major_Linguistics',
 'major_Mathematics',
 'major_Mechanical Engineering',
 'major_Physics',
 'major_Psychology',
 'ml_experience']
```

In [19]:
```
ct.named_transformers_
```

Out[19]:
```
{'standardscaler': StandardScaler(),
 'onehotencoder': OneHotEncoder(),
 'passthrough': 'passthrough',
 'drop': 'drop'}
```

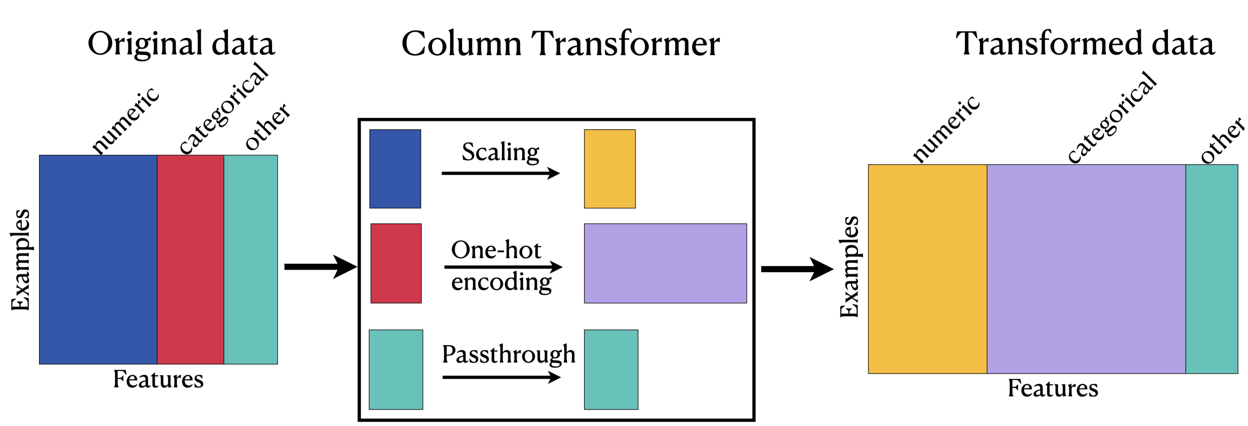
```
Note that the order of the columns in the transformed data depends
upon the order of the features we pass to the `ColumnTransformer` a
nd can be different than the order of the features in the original
dataframe.
```

In [20]:
```
pd.DataFrame(transformed, columns=column_names)
```

Out[20]:

| | university_years | lab1 | lab3 | lab4 | quiz1 | major_Biology | major_Computer Science | ma |
|---|---|---|---|---|---|---|---|---|
| **0** | -0.093454 | 0.358913 | -0.217334 | 0.362700 | 0.840028 | 0.0 | 1.0 | |
| **1** | -1.074719 | 0.590827 | -0.614206 | -0.855972 | 0.712198 | 0.0 | 0.0 | |
| **2** | -0.093454 | -1.264480 | -0.316552 | -1.312974 | -0.693936 | 0.0 | 0.0 | |
| **3** | -0.093454 | 0.242957 | 0.576409 | 0.362700 | 0.456537 | 0.0 | 0.0 | |
| **4** | 0.887812 | -1.380436 | 0.377973 | 0.515034 | -0.054784 | 0.0 | 0.0 | |
| **5** | 1.869077 | -2.192133 | -1.804821 | -2.226978 | -1.844409 | 0.0 | 0.0 | |
| **6** | 0.887812 | -1.032566 | 0.278755 | -0.094302 | 0.712198 | 0.0 | 1.0 | |
| **7** | -0.093454 | 0.706783 | -1.705603 | -1.465308 | -1.333088 | 0.0 | 0.0 | |
| **8** | -1.074719 | 0.938697 | 0.774844 | -1.008306 | -0.693936 | 0.0 | 0.0 | |
| **9** | 0.887812 | 0.706783 | 0.774844 | 0.819702 | -0.054784 | 0.0 | 0.0 | |
| **10** | -0.093454 | 1.054653 | 0.874062 | 0.972036 | -0.949597 | 0.0 | 0.0 | |
| **11** | -2.055985 | 0.706783 | 0.675627 | 0.515034 | -0.054784 | 0.0 | 0.0 | |
| **12** | -1.074719 | 1.054653 | 0.973280 | 1.581372 | 1.862671 | 0.0 | 0.0 | |
| **13** | 0.887812 | 0.706783 | 0.973280 | 0.972036 | 1.862671 | 0.0 | 0.0 | |
| **14** | -0.093454 | 0.706783 | 0.675627 | 0.972036 | -1.972240 | 0.0 | 0.0 | |
| **15** | -0.093454 | 0.358913 | -1.904039 | 0.819702 | 0.840028 | 0.0 | 1.0 | |
| **16** | 1.869077 | -1.612349 | 0.675627 | -0.398970 | -0.054784 | 0.0 | 1.0 | |
| **17** | -0.093454 | -0.336826 | -2.102474 | -0.398970 | 0.200876 | 0.0 | 0.0 | |
| **18** | -1.074719 | 0.242957 | 0.377973 | -0.094302 | -0.438275 | 1.0 | 0.0 | |
| **19** | -1.074719 | -1.380436 | 0.080319 | -1.160640 | 0.456537 | 0.0 | 0.0 | |
| **20** | 0.887812 | 0.822740 | 0.576409 | 1.124370 | 0.200876 | 0.0 | 0.0 | |

### `ColumnTransformer` : Transformed data



[Adapted from here. (https://amueller.github.io/COMS4995-s20/slides/aml-04-preprocessing/#37)](https://amueller.github.io/COMS4995-s20/slides/aml-04-preprocessing/#37)

### Training models with transformed data

- We can now pass the `ColumnTransformer` object as a step in a pipeline.

In [24]:

```
pipe = make_pipeline(ct, SVC())
pipe.fit(X, y)
pipe.predict(X)

#SVC().fit(X, y)
```

Out[24]:

```
array(['A+', 'not A+', 'not A+', 'A+', 'A+', 'not A+', 'A+', 'not A+',
       'not A+', 'A+', 'A+', 'A+', 'A+', 'A+', 'not A+', 'not A+', 'A+',
       'not A+', 'not A+', 'not A+', 'A+'], dtype=object)
```

## ? ? Questions for you

### True/False: `ColumnTransformer`

1. You could carry out cross-validation by passing a `ColumnTransformer` object to `cross_validate`.
2. After applying column transformer, the order of the columns in the transformed data has to be the same as the order of the columns in the original data.
3. After applying a column transformer, the transformed data is always going to be of different shape than the original data.
4. When you call `fit_transform` on a `ColumnTransformer` object, you get a numpy ndarray.

### What transformations on what columns?

Consider the feature columns below.

- What transformations would you apply on each column?

| colour | location | shape | water_content | weight |
|---|---|---|---|---|
| red | canada | NaN | 84 | 100 |
| yellow | mexico | long | 75 | 120 |
| orange | spain | NaN | 90 | NaN |
| magenta | china | round | NaN | 600 |
| purple | austria | NaN | 80 | 115 |
| purple | turkey | oval | 78 | 340 |
| green | mexico | oval | 83 | NaN |

| colour | location | shape | water_content | weight |
|---|---|---|---|---|
| blue | canada | round | 73 | 535 |
| brown | china | NaN | NaN | [illegible] |

# More on feature transformations

## Multiple transformations in a transformer

- Recall that `lab2` has missing values.

In [25]:
```
X.head(10)
```

Out[25]:

| | enjoy_course | ml_experience | major | class_attendance | university_years | lab1 | lab2 | lab3 | la |
|---|---|---|---|---|---|---|---|---|---|
| **0** | yes | 1 | Computer Science | Excellent | 3 | 92 | 93.0 | 84 | |
| **1** | yes | 1 | Mechanical Engineering | Average | 2 | 94 | 90.0 | 80 | |
| **2** | yes | 0 | Mathematics | Poor | 3 | 78 | 85.0 | 83 | |
| **3** | no | 0 | Mathematics | Excellent | 3 | 91 | NaN | 92 | |
| **4** | yes | 0 | Psychology | Good | 4 | 77 | 83.0 | 90 | |
| **5** | no | 1 | Economics | Good | 5 | 70 | 73.0 | 68 | |
| **6** | yes | 1 | Computer Science | Excellent | 4 | 80 | 88.0 | 89 | |
| **7** | no | 0 | Mechanical Engineering | Poor | 3 | 95 | 93.0 | 69 | |
| **8** | no | 0 | Linguistics | Average | 2 | 97 | 90.0 | 94 | |
| **9** | yes | 1 | Mathematics | Average | 4 | 95 | 82.0 | 94 | |

- So we would like to apply more than one transformations on it: imputation and scaling.
- We can treat `lab2` separately, but we can also include it into `numeric_feats` and apply both transformations on all numeric columns.

In [26]:

```
numeric_feats = [
    "university_years",
    "lab1",
    "lab2",
    "lab3",
    "lab4",
    "quiz1",
]  # apply scaling
categorical_feats = ["major"]  # apply one-hot encoding
passthrough_feats = ["ml_experience"]  # do not apply any transformatic
drop_feats = ["class_attendance", "enjoy_course"]
```

- To apply more than one transformations we can define a pipeline inside a column transformer to chain different transformations.

In [27]:

```
ct = make_column_transformer(
    (
        make_pipeline(SimpleImputer(), StandardScaler()),
        numeric_feats,
    ),  # scaling on numeric features
    (OneHotEncoder(), categorical_feats),  # OHE on categorical feature
    ("passthrough", passthrough_feats),  # no transformations on the bi
    ("drop", drop_feats),  # drop the drop features
)
```

In [28]:

```
X_transformed = ct.fit_transform(X)
```

In [29]:

```
column_names = (
    numeric_feats
    + ct.named_transformers_["onehotencoder"].get_feature_names_out().t
    + passthrough_feats
)
column_names
```

Out[29]:

```
['university_years',
 'lab1',
 'lab2',
 'lab3',
 'lab4',
 'quiz1',
 'major_Biology',
 'major_Computer Science',
 'major_Economics',
 'major_Linguistics',
 'major_Mathematics',
 'major_Mechanical Engineering',
 'major_Physics',
 'major_Psychology',
 'ml_experience']
```

In [30]:
```
pd.DataFrame(X_transformed, columns=column_names)
```

Out[30]:

| | university_years | lab1 | lab2 | lab3 | lab4 | quiz1 | major_Biology | major_Cor S |
|---|---|---|---|---|---|---|---|---|
| **0** | -0.093454 | 0.358913 | 0.893260 | -0.217334 | 0.362700 | 0.840028 | 0.0 | |
| **1** | -1.074719 | 0.590827 | 0.294251 | -0.614206 | -0.855972 | 0.712198 | 0.0 | |
| **2** | -0.093454 | -1.264480 | -0.704099 | -0.316552 | -1.312974 | -0.693936 | 0.0 | |
| **3** | -0.093454 | 0.242957 | 0.000000 | 0.576409 | 0.362700 | 0.456537 | 0.0 | |
| **4** | 0.887812 | -1.380436 | -1.103439 | 0.377973 | 0.515034 | -0.054784 | 0.0 | |
| **5** | 1.869077 | -2.192133 | -3.100139 | -1.804821 | -2.226978 | -1.844409 | 0.0 | |
| **6** | 0.887812 | -1.032566 | -0.105089 | 0.278755 | -0.094302 | 0.712198 | 0.0 | |
| **7** | -0.093454 | 0.706783 | 0.893260 | -1.705603 | -1.465308 | -1.333088 | 0.0 | |
| **8** | -1.074719 | 0.938697 | 0.294251 | 0.774844 | -1.008306 | -0.693936 | 0.0 | |
| **9** | 0.887812 | 0.706783 | -1.303109 | 0.774844 | 0.819702 | -0.054784 | 0.0 | |
| **10** | -0.093454 | 1.054653 | -0.504429 | 0.874062 | 0.972036 | -0.949597 | 0.0 | |
| **11** | -2.055985 | 0.706783 | -0.105089 | 0.675627 | 0.515034 | -0.054784 | 0.0 | |
| **12** | -1.074719 | 1.054653 | 1.492270 | 0.973280 | 1.581372 | 1.862671 | 0.0 | |
| **13** | 0.887812 | 0.706783 | 1.092930 | 0.973280 | 0.972036 | 1.862671 | 0.0 | |
| **14** | -0.093454 | 0.706783 | 0.294251 | 0.675627 | 0.972036 | -1.972240 | 0.0 | |
| **15** | -0.093454 | 0.358913 | -0.704099 | -1.904039 | 0.819702 | 0.840028 | 0.0 | |
| **16** | 1.869077 | -1.612349 | 0.493921 | 0.675627 | -0.398970 | -0.054784 | 0.0 | |
| **17** | -0.093454 | -0.336826 | 0.094581 | -2.102474 | -0.398970 | 0.200876 | 0.0 | |
| **18** | -1.074719 | 0.242957 | 0.000000 | 0.377973 | -0.094302 | -0.438275 | 1.0 | |
| **19** | -1.074719 | -1.380436 | 1.092930 | 0.080319 | -1.160640 | 0.456537 | 0.0 | |
| **20** | 0.887812 | 0.822740 | 0.693590 | 0.576409 | 1.124370 | 0.200876 | 0.0 | |

## sklearn set_config

- With multiple transformations in a column transformer, it can get tricky to keep track of everything happening inside it.
- We can use `set_config` to display a diagram of this.

In [31]:
```
from sklearn import set_config

set_config(display="diagram")
```

In [32]:
```
ct
```

Out[32]:
```
ColumnTransformer(transformers=[('pipeline',
                                 Pipeline(steps=[('simpleimputer',
                                                  SimpleImputer()),
                                                 ('standardscaler',
                                                  StandardScaler())]),
                                 ['university_years', 'lab1', 'lab2', 'la
b3',
                                  'lab4', 'quiz1']),
                                ('onehotencoder', OneHotEncoder(), ['majo
r']),
                                ('passthrough', 'passthrough',
                                 ['ml_experience']),
                                ('drop', 'drop',
                                 ['class_attendance', 'enjoy_course'])])
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**
**On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

In [33]:
```
print(ct)
```

```
ColumnTransformer(transformers=[('pipeline',
                                 Pipeline(steps=[('simpleimputer',
                                                  SimpleImputer()),
                                                 ('standardscaler',
                                                  StandardScaler())]),
                                 ['university_years', 'lab1', 'lab2', 'la
b3',
                                  'lab4', 'quiz1']),
                                ('onehotencoder', OneHotEncoder(), ['majo
r']),
                                ('passthrough', 'passthrough',
                                 ['ml_experience']),
                                ('drop', 'drop',
                                 ['class_attendance', 'enjoy_course'])])
```

## Incorporating ordinal feature `class_attendance`

- The `class_attendance` column is different than the `major` column in that there is some ordering of the values.

- Excellent > Good > Average > poor

In [34]:
```
X.head()
```

Out[34]:

| | enjoy_course | ml_experience | major | class_attendance | university_years | lab1 | lab2 | lab3 | la |
|---|---|---|---|---|---|---|---|---|---|
| **0** | yes | 1 | Computer Science | Excellent | 3 | 92 | 93.0 | 84 | |
| **1** | yes | 1 | Mechanical Engineering | Average | 2 | 94 | 90.0 | 80 | |
| **2** | yes | 0 | Mathematics | Poor | 3 | 78 | 85.0 | 83 | |
| **3** | no | 0 | Mathematics | Excellent | 3 | 91 | NaN | 92 | |
| **4** | yes | 0 | Psychology | Good | 4 | 77 | 83.0 | 90 | |

Let's try applying `OrdinalEncoder` on this column.

In [36]:
```
X_toy = X[["class_attendance"]]
enc = OrdinalEncoder()
enc.fit(X_toy)
X_toy_ord = enc.transform(X_toy)
df = pd.DataFrame(
    data=X_toy_ord,
    columns=["class_attendance_enc"],
    index=X_toy.index,
)
```

In [37]:
```
pd.concat([X_toy, df], axis=1).head(10)
```

Out[37]:

| | class_attendance | class_attendance_enc |
|---|---|---|
| **0** | Excellent | 1.0 |
| **1** | Average | 0.0 |
| **2** | Poor | 3.0 |
| **3** | Excellent | 1.0 |
| **4** | Good | 2.0 |
| **5** | Good | 2.0 |
| **6** | Excellent | 1.0 |
| **7** | Poor | 3.0 |
| **8** | Average | 0.0 |
| **9** | Average | 0.0 |

- What's the problem here?
  - The encoder doesn't know the order.
- We can examine unique categories manually, order them based on our intuitions, and then provide this human knowledge to the transformer.

What are the unique categories of `class_attendance` ?

In [38]:
```
X_toy["class_attendance"].unique()
```

Out[38]:
```
array(['Excellent', 'Average', 'Poor', 'Good'], dtype=object)
```

Let's order them manually.

In [39]:
```
class_attendance_levels = ["Poor", "Average", "Good", "Excellent"]
```

```
Note that if you use the reverse order of the categories, it would
n't matter.
```

Let's make sure that we have included all categories in our manual ordering.

In [40]:
```
assert set(class_attendance_levels) == set(X_toy["class_attendance"].un
```

In [41]:
```
oe = OrdinalEncoder(categories=[class_attendance_levels], dtype=int)
oe.fit(X_toy[["class_attendance"]])
ca_transformed = oe.transform(X_toy[["class_attendance"]])
df = pd.DataFrame(
    data=ca_transformed, columns=["class_attendance_enc"], index=X_toy.
)
print(oe.categories_)
pd.concat([X_toy, df], axis=1).head(10)
```

```
[array(['Poor', 'Average', 'Good', 'Excellent'], dtype=object)]
```

Out[41]:

| | class_attendance | class_attendance_enc |
|---|---|---|
| **0** | Excellent | 3 |
| **1** | Average | 1 |
| **2** | Poor | 0 |
| **3** | Excellent | 3 |
| **4** | Good | 2 |
| **5** | Good | 2 |
| **6** | Excellent | 3 |
| **7** | Poor | 0 |
| **8** | Average | 1 |
| **9** | Average | 1 |

The encoded categories are looking better now!

**More than one ordinal columns?**

- We can pass the manually ordered categories when we create an `OrdinalEncoder` object as a list of lists.
- If you have more than one ordinal columns
  - manually create a list of ordered categories for each column
  - pass a list of lists to `OrdinalEncoder`, where each inner list corresponds to manually created list of ordered categories for a corresponding ordinal column.

Now let's incorporate ordinal encoding of `class_attendance` in our column transformer.

In [42]:
```
numeric_feats = [
    "university_years",
    "lab1",
    "lab2",
    "lab3",
    "lab4",
    "quiz1",
]  # apply scaling
categorical_feats = ["major"]  # apply one-hot encoding
ordinal_feats = ["class_attendance"]  # apply ordinal encoding
passthrough_feats = ["ml_experience"]  # do not apply any transformatic
drop_feats = ["enjoy_course"]  # do not include these features
```

In [43]:
```
ct = make_column_transformer(
    (
        make_pipeline(SimpleImputer(), StandardScaler()),
        numeric_feats,
    ),  # scaling on numeric features
    (OneHotEncoder(), categorical_feats),  # OHE on categorical feature
    (
        OrdinalEncoder(categories=[class_attendance_levels], dtype=int)
        ordinal_feats,
    ),  # Ordinal encoding on ordinal features
    ("passthrough", passthrough_feats),  # no transformations on the bi
    ("drop", drop_feats),  # drop the drop features
)
```

In [44]:
```
ct
```

Out[44]:
```
ColumnTransformer(transformers=[('pipeline',
                                 Pipeline(steps=[('simpleimputer',
                                                  SimpleImputer()),
                                                 ('standardscaler',
                                                  StandardScaler())]),
                                 ['university_years', 'lab1', 'lab2', 'la
b3',
                                  'lab4', 'quiz1']),
                                ('onehotencoder', OneHotEncoder(), ['majo
r']),
                                ('ordinalencoder',
                                 OrdinalEncoder(categories=[['Poor', 'Ave
rage',
                                                             'Good',
                                                             'Excellen
t']],
                                                dtype=<class 'int'>),
                                 ['class_attendance']),
                                ('passthrough', 'passthrough',
                                 ['ml_experience']),
                                ('drop', 'drop', ['enjoy_course'])])
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**
**On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

In [45]:
```
X_transformed = ct.fit_transform(X)
```

In [46]:
```
column_names = (
    numeric_feats
    + ct.named_transformers_["onehotencoder"].get_feature_names_out().t
    + ordinal_feats
    + passthrough_feats
)
column_names
```

Out[46]:
```
['university_years',
 'lab1',
 'lab2',
 'lab3',
 'lab4',
 'quiz1',
 'major_Biology',
 'major_Computer Science',
 'major_Economics',
 'major_Linguistics',
 'major_Mathematics',
 'major_Mechanical Engineering',
 'major_Physics',
 'major_Psychology',
 'class_attendance',
 'ml_experience']
```

In [47]:
```
pd.DataFrame(X_transformed, columns=column_names)
```

Out[47]:

| | university_years | lab1 | lab2 | lab3 | lab4 | quiz1 | major_Biology | major_Cor S |
|---|---|---|---|---|---|---|---|---|
| **0** | -0.093454 | 0.358913 | 0.893260 | -0.217334 | 0.362700 | 0.840028 | 0.0 | |
| **1** | -1.074719 | 0.590827 | 0.294251 | -0.614206 | -0.855972 | 0.712198 | 0.0 | |
| **2** | -0.093454 | -1.264480 | -0.704099 | -0.316552 | -1.312974 | -0.693936 | 0.0 | |
| **3** | -0.093454 | 0.242957 | 0.000000 | 0.576409 | 0.362700 | 0.456537 | 0.0 | |
| **4** | 0.887812 | -1.380436 | -1.103439 | 0.377973 | 0.515034 | -0.054784 | 0.0 | |
| **5** | 1.869077 | -2.192133 | -3.100139 | -1.804821 | -2.226978 | -1.844409 | 0.0 | |
| **6** | 0.887812 | -1.032566 | -0.105089 | 0.278755 | -0.094302 | 0.712198 | 0.0 | |
| **7** | -0.093454 | 0.706783 | 0.893260 | -1.705603 | -1.465308 | -1.333088 | 0.0 | |
| **8** | -1.074719 | 0.938697 | 0.294251 | 0.774844 | -1.008306 | -0.693936 | 0.0 | |
| **9** | 0.887812 | 0.706783 | -1.303109 | 0.774844 | 0.819702 | -0.054784 | 0.0 | |
| **10** | -0.093454 | 1.054653 | -0.504429 | 0.874062 | 0.972036 | -0.949597 | 0.0 | |
| **11** | -2.055985 | 0.706783 | -0.105089 | 0.675627 | 0.515034 | -0.054784 | 0.0 | |
| **12** | -1.074719 | 1.054653 | 1.492270 | 0.973280 | 1.581372 | 1.862671 | 0.0 | |
| **13** | 0.887812 | 0.706783 | 1.092930 | 0.973280 | 0.972036 | 1.862671 | 0.0 | |
| **14** | -0.093454 | 0.706783 | 0.294251 | 0.675627 | 0.972036 | -1.972240 | 0.0 | |
| **15** | -0.093454 | 0.358913 | -0.704099 | -1.904039 | 0.819702 | 0.840028 | 0.0 | |
| **16** | 1.869077 | -1.612349 | 0.493921 | 0.675627 | -0.398970 | -0.054784 | 0.0 | |
| **17** | -0.093454 | -0.336826 | 0.094581 | -2.102474 | -0.398970 | 0.200876 | 0.0 | |
| **18** | -1.074719 | 0.242957 | 0.000000 | 0.377973 | -0.094302 | -0.438275 | 1.0 | |
| **19** | -1.074719 | -1.380436 | 1.092930 | 0.080319 | -1.160640 | 0.456537 | 0.0 | |
| **20** | 0.887812 | 0.822740 | 0.693590 | 0.576409 | 1.124370 | 0.200876 | 0.0 | |

## Dealing with unknown categories

Let's create a pipeline with the column transformer and pass it to `cross_validate` .

In [48]:
```
pipe = make_pipeline(ct, SVC())
```

In [49]:

```
scores = cross_validate(pipe, X, y, return_train_score=True)
pd.DataFrame(scores)
```

```
/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packages/sklea
rn/model_selection/_validation.py:776: UserWarning: Scoring failed. The s
core on this train-test partition for these parameters will be set to na
n. Details:
Traceback (most recent call last):
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/sklearn/model_selection/_validation.py", line 767, in _score
    scores = scorer(estimator, X_test, y_test)
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/sklearn/metrics/_scorer.py", line 429, in _passthrough_scorer
    return estimator.score(*args, **kwargs)
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/sklearn/pipeline.py", line 695, in score
    Xt = transform.transform(Xt)
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/sklearn/compose/_column_transformer.py", line 763, in transform
    Xs = self._fit_transform(
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/sklearn/compose/_column_transformer.py", line 621, in _fit_transform
    return Parallel(n_jobs=self.n_jobs)(
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/joblib/parallel.py", line 1051, in __call__
    while self.dispatch_one_batch(iterator):
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/joblib/parallel.py", line 864, in dispatch_one_batch
    self._dispatch(tasks)
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/joblib/parallel.py", line 782, in _dispatch
    job = self._backend.apply_async(batch, callback=cb)
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/joblib/_parallel_backends.py", line 208, in apply_async
    result = ImmediateResult(func)
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/joblib/_parallel_backends.py", line 572, in __init__
    self.results = batch()
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/joblib/parallel.py", line 263, in __call__
    return [func(*args, **kwargs)
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/joblib/parallel.py", line 263, in <listcomp>
    return [func(*args, **kwargs)
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/sklearn/utils/fixes.py", line 117, in __call__
    return self.function(*args, **kwargs)
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/sklearn/pipeline.py", line 853, in _transform_one
    res = transformer.transform(X)
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/sklearn/preprocessing/_encoders.py", line 882, in transform
    X_int, X_mask = self._transform(
  File "/Users/mathias/miniconda3/envs/cpsc330/lib/python3.10/site-packag
es/sklearn/preprocessing/_encoders.py", line 160, in _transform
    raise ValueError(msg)
ValueError: Found unknown categories ['Biology'] in column 0 during trans
form
```

```
warnings.warn(
```

Out[49]:

| | fit_time | score_time | test_score | train_score |
|---|---|---|---|---|
| **0** | 0.013106 | 0.006488 | 1.00 | 0.937500 |
| **1** | 0.010220 | 0.005606 | 1.00 | 0.941176 |
| **2** | 0.008559 | 0.005460 | 0.50 | 1.000000 |
| **3** | 0.007937 | 0.004804 | 0.75 | 0.941176 |
| **4** | 0.008821 | 0.024068 | NaN | 1.000000 |

- What's going on here??
- Let's look at the error message: `ValueError: Found unknown categories ['Biology'] in column 0 during transform`

In [50]:

```
X["major"].value_counts()
```

Out[50]:

```
Computer Science          4
Mathematics               4
Mechanical Engineering    3
Psychology                3
Economics                 2
Linguistics               2
Physics                   2
Biology                   1
Name: major, dtype: int64
```

- There is only one instance of Biology.
- During cross-validation, this is getting put into the validation split.
- By default, `OneHotEncoder` throws an error because you might want to know about this.

Simplest fix:

- Pass `handle_unknown="ignore"` argument to `OneHotEncoder`
- It creates a row with all zeros.

In [51]:
```
ct = make_column_transformer(
    (
        make_pipeline(SimpleImputer(), StandardScaler()),
        numeric_feats,
    ),  # scaling on numeric features
    (
        OneHotEncoder(handle_unknown="ignore"),
        categorical_feats,
    ),  # OHE on categorical features
    (
        OrdinalEncoder(categories=[class_attendance_levels], dtype=int)
        ordinal_feats,
    ),  # Ordinal encoding on ordinal features
    ("passthrough", passthrough_feats),  # no transformations on the bi
    ("drop", drop_feats),  # drop the drop features
)
```

In [52]:
```
ct
```

Out[52]:
```
ColumnTransformer(transformers=[('pipeline',
                                 Pipeline(steps=[('simpleimputer',
                                                  SimpleImputer()),
                                                 ('standardscaler',
                                                  StandardScaler())]),
                                 ['university_years', 'lab1', 'lab2', 'la
b3',
                                  'lab4', 'quiz1']),
                                ('onehotencoder',
                                 OneHotEncoder(handle_unknown='ignore'),
                                 ['major']),
                                ('ordinalencoder',
                                 OrdinalEncoder(categories=[['Poor', 'Ave
rage',
                                                             'Good',
                                                             'Excellen
t']],
                                                dtype=<class 'int'>),
                                 ['class_attendance']),
                                ('passthrough', 'passthrough',
                                 ['ml_experience']),
                                ('drop', 'drop', ['enjoy_course'])])
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**
**On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

In [53]:
```
pipe = make_pipeline(ct, SVC())
```

In [54]:
```
scores = cross_validate(pipe, X, y, cv=5, return_train_score=True)
pd.DataFrame(scores)
```

Out[54]:

| | fit_time | score_time | test_score | train_score |
|---|---|---|---|---|
| **0** | 0.010619 | 0.006246 | 1.00 | 0.937500 |
| **1** | 0.011235 | 0.005561 | 1.00 | 0.941176 |
| **2** | 0.009199 | 0.005520 | 0.50 | 1.000000 |
| **3** | 0.009306 | 0.005152 | 0.75 | 0.941176 |
| **4** | 0.008154 | 0.004914 | 0.75 | 1.000000 |

- With this approach, all unknown categories will be represented with all zeros and cross-validation is running OK now.

Ask yourself the following questions when you work with categorical variables

- Do you want this behaviour?
- Are you expecting to get many unknown categories? Do you want to be able to distinguish between them?

**Cases where it's OK to break the golden rule**

- If it's some fix number of categories. For example, if it's something like provinces in Canada or majors taught at UBC. We know the categories in advance and this is one of the cases where it might be OK to violate the golden rule and get a list of all possible values for the categorical variable.

## Categorical features with only two possible categories

- Sometimes you have features with only two possible categories.
- If we apply `OheHotEncoder` on such columns, it'll create two columns, which seems wasteful, as we could represent all information in the column in just one column with say 0's and 1's with presence of absence of one of one of the categories.
- You can pass `drop="if_binary"` argument to `OneHotEncoder` in order to create only one column in such scenario.

In [55]:
```python
X["enjoy_course"].head()
```

Out[55]:
```
0    yes
1    yes
2    yes
3     no
4    yes
Name: enjoy_course, dtype: object
```

In [56]:
```python
ohe_enc = OneHotEncoder(drop="if_binary", dtype=int, sparse=False)
ohe_enc.fit(X[["enjoy_course"]])
transformed = ohe_enc.transform(X[["enjoy_course"]])
df = pd.DataFrame(data=transformed, columns=["enjoy_course_enc"], index
pd.concat([X[["enjoy_course"]], df], axis=1).head(10)
```

Out[56]:

| | enjoy_course | enjoy_course_enc |
|---|---|---|
| **0** | yes | 1 |
| **1** | yes | 1 |
| **2** | yes | 1 |
| **3** | no | 0 |
| **4** | yes | 1 |
| **5** | no | 0 |
| **6** | yes | 1 |
| **7** | no | 0 |
| **8** | no | 0 |
| **9** | yes | 1 |

In [57]:
```python
numeric_feats = [
    "university_years",
    "lab1",
    "lab2",
    "lab3",
    "lab4",
    "quiz1",
]  # apply scaling
categorical_feats = ["major"]  # apply one-hot encoding
ordinal_feats = ["class_attendance"]  # apply ordinal encoding
binary_feats = ["enjoy_course"]  # apply one-hot encoding with drop="if
passthrough_feats = ["ml_experience"]  # do not apply any transformatic
drop_feats = []
```

In [59]:
```
ct = make_column_transformer(
    (
        make_pipeline(SimpleImputer(), StandardScaler()),
        numeric_feats,
    ),  # scaling on numeric features
    (
        OneHotEncoder(handle_unknown="ignore"),
        categorical_feats,
    ),  # OHE on categorical features
    (
        OrdinalEncoder(categories=[class_attendance_levels], dtype=int)
        ordinal_feats,
    ),  # Ordinal encoding on ordinal features
    (
        OneHotEncoder(drop="if_binary", dtype=int),
        binary_feats,
    ),  # OHE on categorical features
    ("passthrough", passthrough_feats),  # no transformations on the bi
)
```

In [60]:
```
ct
```

Out[60]:
```
ColumnTransformer(transformers=[('pipeline',
                                 Pipeline(steps=[('simpleimputer',
                                                  SimpleImputer()),
                                                 ('standardscaler',
                                                  StandardScaler())]),
                                 ['university_years', 'lab1', 'lab2', 'la
b3',
                                  'lab4', 'quiz1']),
                                ('onehotencoder-1',
                                 OneHotEncoder(handle_unknown='ignore'),
                                 ['major']),
                                ('ordinalencoder',
                                 OrdinalEncoder(categories=[['Poor', 'Ave
rage',
                                                             'Good',
                                                             'Excellen
t']],
                                                dtype=<class 'int'>),
                                 ['class_attendance']),
                                ('onehotencoder-2',
                                 OneHotEncoder(drop='if_binary',
                                               dtype=<class 'int'>),
                                 ['enjoy_course']),
                                ('passthrough', 'passthrough',
                                 ['ml_experience'])])
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**
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In [61]:
```
pipe = make_pipeline(ct, SVC())
```

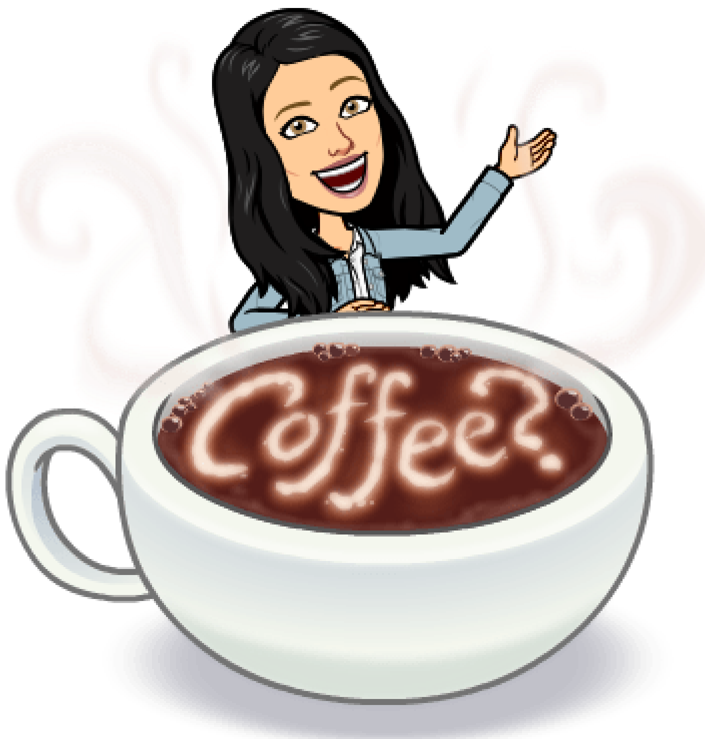
In [62]:
```
scores = cross_validate(pipe, X, y, cv=5, return_train_score=True)
pd.DataFrame(scores)
```

Out[62]:

| | fit_time | score_time | test_score | train_score |
|---|---|---|---|---|
| **0** | 0.013232 | 0.008059 | 1.00 | 1.000000 |
| **1** | 0.011555 | 0.006521 | 1.00 | 0.941176 |
| **2** | 0.010359 | 0.006901 | 0.50 | 1.000000 |
| **3** | 0.010653 | 0.006728 | 1.00 | 0.941176 |
| **4** | 0.009934 | 0.006208 | 0.75 | 1.000000 |

```
Do not read too much into the scores, as we are running cross-valid
ation on a very small dataset with 21 examples. The main point here
is to show you how can we use `ColumnTransformer` to apply differen
t transformations on different columns.
```

## Break (5 min)



# `ColumnTransformer` on the California housing dataset

In [63]:

```
housing_df = pd.read_csv("../data/housing.csv")
train_df, test_df = train_test_split(housing_df, test_size=0.1, random_

train_df.head()
```

Out[63]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households |
|---|---|---|---|---|---|---|---|
| **6051** | -117.75 | 34.04 | 22.0 | 2948.0 | 636.0 | 2600.0 | 602.( |
| **20113** | -119.57 | 37.94 | 17.0 | 346.0 | 130.0 | 51.0 | 20.( |
| **14289** | -117.13 | 32.74 | 46.0 | 3355.0 | 768.0 | 1457.0 | 708.( |
| **13665** | -117.31 | 34.02 | 18.0 | 1634.0 | 274.0 | 899.0 | 285.( |
| **14471** | -117.23 | 32.88 | 18.0 | 5566.0 | 1465.0 | 6303.0 | 1458.( |

Some column values are mean/median but some are not.

Let's add some new features to the dataset which could help predicting the target: `median_house_value`.

In [64]:

```
train_df = train_df.assign(
    rooms_per_household=train_df["total_rooms"] / train_df["households"
)
test_df = test_df.assign(
    rooms_per_household=test_df["total_rooms"] / test_df["households"]
)

train_df = train_df.assign(
    bedrooms_per_household=train_df["total_bedrooms"] / train_df["house
)
test_df = test_df.assign(
    bedrooms_per_household=test_df["total_bedrooms"] / test_df["househo
)

train_df = train_df.assign(
    population_per_household=train_df["population"] / train_df["househo
)
test_df = test_df.assign(
    population_per_household=test_df["population"] / test_df["household
)
```

In [65]:
```
train_df.head()
```

Out[65]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households |
|---|---|---|---|---|---|---|---|
| **6051** | -117.75 | 34.04 | 22.0 | 2948.0 | 636.0 | 2600.0 | 602.0 |
| **20113** | -119.57 | 37.94 | 17.0 | 346.0 | 130.0 | 51.0 | 20.0 |
| **14289** | -117.13 | 32.74 | 46.0 | 3355.0 | 768.0 | 1457.0 | 708.0 |
| **13665** | -117.31 | 34.02 | 18.0 | 1634.0 | 274.0 | 899.0 | 285.0 |
| **14471** | -117.23 | 32.88 | 18.0 | 5566.0 | 1465.0 | 6303.0 | 1458.0 |

In [66]:
```
# Let's keep both numeric and categorical columns in the data.
X_train = train_df.drop(columns=["median_house_value"])
y_train = train_df["median_house_value"]

X_test = test_df.drop(columns=["median_house_value"])
y_test = test_df["median_house_value"]
```

In [67]:
```
from sklearn.compose import ColumnTransformer, make_column_transformer
```

In [68]:
```
X_train.head(10)
```

Out[68]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households |
|---|---|---|---|---|---|---|---|
| **6051** | -117.75 | 34.04 | 22.0 | 2948.0 | 636.0 | 2600.0 | 602.0 |
| **20113** | -119.57 | 37.94 | 17.0 | 346.0 | 130.0 | 51.0 | 20.0 |
| **14289** | -117.13 | 32.74 | 46.0 | 3355.0 | 768.0 | 1457.0 | 708.0 |
| **13665** | -117.31 | 34.02 | 18.0 | 1634.0 | 274.0 | 899.0 | 285.0 |
| **14471** | -117.23 | 32.88 | 18.0 | 5566.0 | 1465.0 | 6303.0 | 1458.0 |
| **9730** | -121.74 | 36.79 | 16.0 | 3841.0 | 620.0 | 1799.0 | 611.0 |
| **14690** | -117.09 | 32.80 | 36.0 | 2163.0 | 367.0 | 915.0 | 360.0 |
| **7938** | -118.11 | 33.86 | 33.0 | 2389.0 | 410.0 | 1229.0 | 393.0 |
| **18365** | -122.12 | 37.28 | 21.0 | 349.0 | 64.0 | 149.0 | 56.0 |
| **10931** | -117.91 | 33.74 | 25.0 | 4273.0 | 965.0 | 2946.0 | 922.0 |

In [69]:
```
X_train.columns
```

Out[69]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'ocean_proximity', 'rooms_per_household', 'bedrooms_per_househol
d',
       'population_per_household'],
      dtype='object')
```

In [70]:
```python
# Identify the categorical and numeric columns
numeric_features = [
    "longitude",
    "latitude",
    "housing_median_age",
    "total_rooms",
    "total_bedrooms",
    "population",
    "households",
    "median_income",
    "rooms_per_household",
    "bedrooms_per_household",
    "population_per_household",
]

categorical_features = ["ocean_proximity"]
target = "median_income"
```

- Let's create a `ColumnTransformer` for our dataset.

In [71]:
```python
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18576 entries, 6051 to 19966
Data columns (total 12 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   longitude                 18576 non-null  float64
 1   latitude                  18576 non-null  float64
 2   housing_median_age        18576 non-null  float64
 3   total_rooms               18576 non-null  float64
 4   total_bedrooms            18391 non-null  float64
 5   population                18576 non-null  float64
 6   households                18576 non-null  float64
 7   median_income             18576 non-null  float64
 8   ocean_proximity           18576 non-null  object 
 9   rooms_per_household       18576 non-null  float64
 10  bedrooms_per_household    18391 non-null  float64
 11  population_per_household  18576 non-null  float64
dtypes: float64(11), object(1)
memory usage: 1.8+ MB
```

In [72]:
```python
X_train["ocean_proximity"].value_counts()
```

Out[72]:
```
<1H OCEAN     8221
INLAND        5915
NEAR OCEAN    2389
NEAR BAY      2046
ISLAND           5
Name: ocean_proximity, dtype: int64
```

In [73]:
```python
numeric_transformer = make_pipeline(SimpleImputer(strategy="median"), S
categorical_transformer = OneHotEncoder(handle_unknown="ignore")

preprocessor = make_column_transformer(
    (numeric_transformer, numeric_features),
    (categorical_transformer, categorical_features),
)
```

In [74]:
```python
preprocessor
```

Out[74]:
```
ColumnTransformer(transformers=[('pipeline',
                                 Pipeline(steps=[('simpleimputer',
                                                  SimpleImputer(strategy
='median')),
                                                 ('standardscaler',
                                                  StandardScaler())]),
                                 ['longitude', 'latitude', 'housing_media
n_age',
                                  'total_rooms', 'total_bedrooms', 'popul
ation',
                                  'households', 'median_income',
                                  'rooms_per_household',
                                  'bedrooms_per_household',
                                  'population_per_household']),
                                ('onehotencoder',
                                 OneHotEncoder(handle_unknown='ignore'),
                                 ['ocean_proximity'])])
```

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In [75]:
```python
X_train_pp = preprocessor.fit_transform(X_train)
```

- When we `fit` the preprocessor, it calls `fit` on *all* the transformers
- When we `transform` the preprocessor, it calls `transform` on *all* the transformers.

We can get the new names of the columns that were generated by the one-hot encoding:

In [76]:
```
preprocessor
```

Out[76]:
```
ColumnTransformer(transformers=[('pipeline',
                                 Pipeline(steps=[('simpleimputer',
                                                  SimpleImputer(strategy
='median')),
                                                 ('standardscaler',
                                                  StandardScaler())]),
                                 ['longitude', 'latitude', 'housing_media
n_age',
                                  'total_rooms', 'total_bedrooms', 'popul
ation',
                                  'households', 'median_income',
                                  'rooms_per_household',
                                  'bedrooms_per_household',
                                  'population_per_household']),
                                ('onehotencoder',
                                 OneHotEncoder(handle_unknown='ignore'),
                                 ['ocean_proximity'])])
```

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In [77]:
```
preprocessor.named_transformers_["onehotencoder"].get_feature_names_out
    categorical_features
)
```

Out[77]:
```
array(['ocean_proximity_<1H OCEAN', 'ocean_proximity_INLAND',
       'ocean_proximity_ISLAND', 'ocean_proximity_NEAR BAY',
       'ocean_proximity_NEAR OCEAN'], dtype=object)
```

Combining this with the numeric feature names gives us all the column names:

In [78]:
```python
column_names = numeric_features + list(
    preprocessor.named_transformers_["onehotencoder"].get_feature_names
        categorical_features
    )
)
column_names
```

Out[78]:
```
['longitude',
 'latitude',
 'housing_median_age',
 'total_rooms',
 'total_bedrooms',
 'population',
 'households',
 'median_income',
 'rooms_per_household',
 'bedrooms_per_household',
 'population_per_household',
 'ocean_proximity_<1H OCEAN',
 'ocean_proximity_INLAND',
 'ocean_proximity_ISLAND',
 'ocean_proximity_NEAR BAY',
 'ocean_proximity_NEAR OCEAN']
```

Let's visualize the preprocessed training data as a dataframe.

In [79]:
```python
pd.DataFrame(X_train_pp, columns=column_names)
```

Out[79]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | househo |
|---|---|---|---|---|---|---|---|
| **0** | 0.908140 | -0.743917 | -0.526078 | 0.143120 | 0.235339 | 1.026092 | 0.2661 |
| **1** | -0.002057 | 1.083123 | -0.923283 | -1.049510 | -0.969959 | -1.206672 | -1.253 |
| **2** | 1.218207 | -1.352930 | 1.380504 | 0.329670 | 0.549764 | 0.024896 | 0.542 |
| **3** | 1.128188 | -0.753286 | -0.843842 | -0.459154 | -0.626949 | -0.463877 | -0.561 |
| **4** | 1.168196 | -1.287344 | -0.843842 | 1.343085 | 2.210026 | 4.269688 | 2.500 |
| **...** | ... | ... | ... | ... | ... | ... | |
| **18571** | 0.733102 | -0.804818 | 0.586095 | -0.875337 | -0.243446 | -0.822136 | -0.9661 |
| **18572** | 1.163195 | -1.057793 | -1.161606 | 0.940194 | 0.609314 | 0.882438 | 0.728 |
| **18573** | -1.097293 | 0.797355 | -1.876574 | 0.695434 | 0.433046 | 0.881563 | 0.5141 |
| **18574** | -1.437367 | 1.008167 | 1.221622 | -0.499947 | -0.484029 | -0.759944 | -0.454 |
| **18575** | 0.242996 | 0.272667 | -0.684960 | -0.332190 | -0.353018 | -0.164307 | -0.396 |

18576 rows × 16 columns

In [80]:
```
results_dict = {}
dummy = DummyRegressor()
results_dict["dummy"] = mean_std_cross_val_scores(
    dummy, X_train, y_train, return_train_score=True
)
pd.DataFrame(results_dict).T
```

Out[80]:

| | fit_time | score_time | test_score | train_score |
|---|---|---|---|---|
| **dummy** | 0.002 (+/- 0.001) | 0.000 (+/- 0.000) | -0.001 (+/- 0.001) | 0.000 (+/- 0.000) |

In [81]:
```
from sklearn.svm import SVR

knn_pipe = make_pipeline(preprocessor, KNeighborsRegressor())
```

In [82]:
```
knn_pipe
```

Out[82]:
```
Pipeline(steps=[('columntransformer',
                 ColumnTransformer(transformers=[('pipeline',
                                                  Pipeline(steps=[('simpl
eimputer',
                                                                   Simple
Imputer(strategy='median')),
                                                                  ('stand
ardscaler',
                                                                   Standa
rdScaler())]),
                                                  ['longitude', 'latitud
e',
                                                   'housing_median_age',
                                                   'total_rooms',
                                                   'total_bedrooms',
                                                   'population', 'househo
lds',
                                                   'median_income',
                                                   'rooms_per_household',
                                                   'bedrooms_per_househol
d',
                                                   'population_per_househ
old']),
                                                 ('onehotencoder',
                                                  OneHotEncoder(handle_un
known='ignore'),
                                                  ['ocean_proximit
y'])])),
                ('kneighborsregressor', KNeighborsRegressor())])
```

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In [83]:
```
results_dict["imp + scaling + ohe + KNN"] = mean_std_cross_val_scores(
    knn_pipe, X_train, y_train, return_train_score=True
)
```

In [84]:
```
pd.DataFrame(results_dict).T
```

Out[84]:

| | fit_time | score_time | test_score | train_score |
|---|---|---|---|---|
| **dummy** | 0.002 (+/- 0.001) | 0.000 (+/- 0.000) | -0.001 (+/- 0.001) | 0.000 (+/- 0.000) |
| **imp + scaling + ohe + KNN** | 0.029 (+/- 0.005) | 0.087 (+/- 0.074) | 0.721 (+/- 0.012) | 0.816 (+/- 0.006) |

In [85]:
```
svr_pipe = make_pipeline(preprocessor, SVR())
results_dict["imp + scaling + ohe + SVR (default)"] = mean_std_cross_va
    svr_pipe, X_train, y_train, return_train_score=True
)
```

In [86]:
```
pd.DataFrame(results_dict).T
```

Out[86]:

| | fit_time | score_time | test_score | train_score |
|---|---|---|---|---|
| **dummy** | 0.002 (+/- 0.001) | 0.000 (+/- 0.000) | -0.001 (+/- 0.001) | 0.000 (+/- 0.000) |
| **imp + scaling + ohe + KNN** | 0.029 (+/- 0.005) | 0.087 (+/- 0.074) | 0.721 (+/- 0.012) | 0.816 (+/- 0.006) |
| **imp + scaling + ohe + SVR (default)** | 10.170 (+/- 0.184) | 4.659 (+/- 0.107) | -0.049 (+/- 0.012) | -0.049 (+/- 0.001) |

The results with `scikit-learn`'s default SVR hyperparameters are pretty bad (negative $R^2$, worse than predicting the mean!).

**What should we try for hyper-parameters?**

In [87]:
```
svr_C_pipe = make_pipeline(preprocessor, SVR(C=10000))
results_dict["imp + scaling + ohe + SVR (C=10000)"] = mean_std_cross_va
    svr_C_pipe, X_train, y_train, return_train_score=True
)
```

In [88]:
```
pd.DataFrame(results_dict).T
```

Out[88]:

| | fit_time | score_time | test_score | train_score |
|---|---|---|---|---|
| **dummy** | 0.002 (+/- 0.001) | 0.000 (+/- 0.000) | -0.001 (+/- 0.001) | 0.000 (+/- 0.000) |
| **imp + scaling + ohe + KNN** | 0.029 (+/- 0.005) | 0.087 (+/- 0.074) | 0.721 (+/- 0.012) | 0.816 (+/- 0.006) |
| **imp + scaling + ohe + SVR (default)** | 10.170 (+/- 0.184) | 4.659 (+/- 0.107) | -0.049 (+/- 0.012) | -0.049 (+/- 0.001) |
| **imp + scaling + ohe + SVR (C=10000)** | 9.368 (+/- 0.159) | 4.685 (+/- 0.171) | 0.721 (+/- 0.007) | 0.726 (+/- 0.007) |

With a bigger value for `C` the results are much better. We need to carry out systematic hyperparameter optimization to get better results. (Coming up next week.)

- Note that categorical features are different than free text features. Sometimes there are columns containing free text information and we we'll look at ways to deal with them in the later part of this lecture.

## OHE with many categories

- Do we have enough data for rare categories to learn anything meaningful?
- How about grouping them into bigger categories?
  - Example: country names into continents such as "South America" or "Asia"
- Or having "other" category for rare cases?

## Do we actually want to use certain features for prediction?

- Do you want to use certain features such as **gender** or **race** in prediction?
- Remember that the systems you build are going to be used in some applications.
- It's extremely important to be mindful of the consequences of including certain features in your predictive model.

## Preprocessing the targets?

- Generally no need for this when doing classification.
- In regression it makes sense in some cases. More on this later.
- `sklearn` is fine with categorical labels ($y$-values) for classification problems.

## ❓❓ Questions for you

#### True/False: Categorical features

1. `handle_unknown="ignore"` would treat all unknown categories equally.
2. Creating groups of rarely occurring categories might overfit the model.

# Encoding text data

In [90]:
```
toy_spam = [
    [
        "URGENT!! As a valued network customer you have been selected t
        "spam",
    ],
    ["Lol you are always so convincing.", "non spam"],
    ["Nah I don't think he goes to usf, he lives around here though", "
    [
        "URGENT! You have won a 1 week FREE membership in our £100000 p
        "spam",
    ],
    [
        "Had your mobile 11 months or more? U R entitled to Update to t
        "spam",
    ],
    ["Congrats! I can't wait to see you!!", "non spam"],
]
toy_df = pd.DataFrame(toy_spam, columns=["sms", "target"])
```

## Spam/non spam toy example

- What if the feature is in the form of raw text?
- The feature `sms` below is neither categorical nor ordinal.
- How can we encode it so that we can pass it to the machine learning algorithms we have seen so far?

In [91]:
```
toy_df
```

Out[91]:

| | sms | target |
|---|---|---|
| **0** | URGENT!! As a valued network customer you have been selected to receive a £900 prize reward! | spam |
| **1** | Lol you are always so convincing. | non spam |
| **2** | Nah I don't think he goes to usf, he lives around here though | non spam |
| **3** | URGENT! You have won a 1 week FREE membership in our £100000 prize Jackpot! | spam |
| **4** | Had your mobile 11 months or more? U R entitled to Update to the latest colour mobiles with camera for Free! Call The Mobile Update Co FREE on 08002986030 | spam |
| **5** | Congrats! I can't wait to see you!! | non spam |

## What if we apply OHE?

In [92]:
```
### DO NOT DO THIS.
enc = OneHotEncoder(sparse=False)
transformed = enc.fit_transform(toy_df[["sms"]])
pd.DataFrame(transformed, columns=enc.categories_)
```

Out[92]:

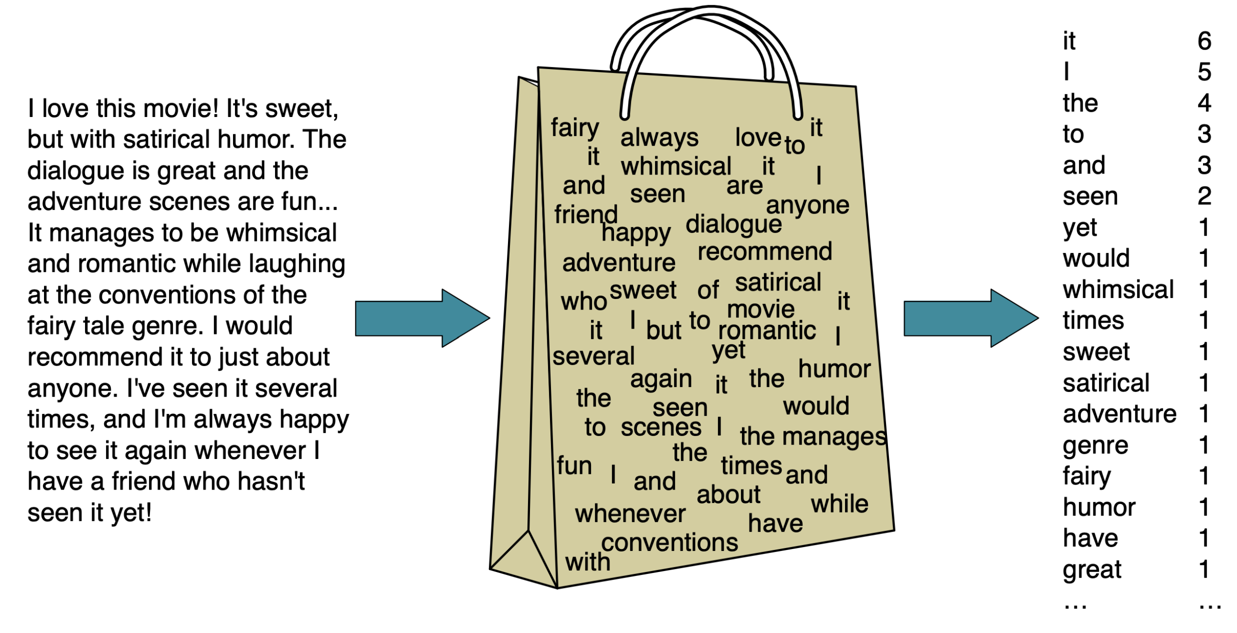
| | Congrats! I can't wait to see you!! | Had your mobile 11 months or more? U R entitled to Update to the latest colour mobiles with camera for Free! Call The Mobile Update Co FREE on 08002986030 | Lol you are always so convincing. | Nah I don't think he goes to usf, he lives around here though | URGENT! You have won a 1 week FREE membership in our £100000 prize Jackpot! | URGENT!! As a valued network customer you have been selected to receive a £900 prize reward! |
|---|---|---|---|---|---|---|
| **0** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| **1** | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 |
| **2** | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 |
| **3** | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 |
| **4** | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **5** | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

- We do not have a fixed number of categories here.
- Each "category" (feature value) is likely to occur only once in the training data and we won't learn anything meaningful if we apply one-hot encoding or ordinal encoding on this feature.

- How can we encode or represent raw text data into fixed number of features so that we can learn some useful patterns from it?
- This is a well studied problem in the field of Natural Language Processing (NLP), which is concerned with giving computers the ability to understand written and spoken language.
- Some popular representations of raw text include:
  - **Bag of words**
  - TF-IDF
  - Embedding representations

## Bag of words (BOW) representation

- One of the most popular representation of raw text
- Ignores the syntax and word order
- It has two components:
  - The vocabulary (all unique words in all documents)
  - A value indicating either the presence or absence or the count of each word in the document.




## Extracting BOW features using `scikit-learn`

- `CountVectorizer`
  - Converts a collection of text documents to a matrix of word counts.
  - Each row represents a "document" (e.g., a text message in our example).
  - Each column represents a word in the vocabulary (the set of unique words) in the training data.
  - Each cell represents how often the word occurs in the document.

In the Natural Language Processing (NLP) community text data is referred to as a **corpus** (plural: corpora).

In [93]:

```
from sklearn.feature_extraction.text import CountVectorizer

vec = CountVectorizer()
X_counts = vec.fit_transform(toy_df["sms"])
bow_df = pd.DataFrame(
    X_counts.toarray(), columns=vec.get_feature_names_out(), index=toy_
)
bow_df
```

Out[93]:

| sms | 08002986030 | 100000 | 11 | 900 | always | are | around | as | been | call | ... | update | urgen |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **URGENT!! As a valued network customer you have been selected to receive a £900 prize reward!** | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | ... | 0 | |
| **Lol you are always so convincing.** | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | ... | 0 | [illegible] |
| **Nah I don't think he goes to usf, he lives around here though** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | ... | 0 | [illegible] |
| **URGENT! You have won a 1 week FREE membership in our £100000 prize Jackpot!** | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | |
| **Had your mobile 11 months or more? U R entitled to Update to the latest colour mobiles with camera for Free! Call The Mobile Update Co FREE on 08002986030** | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | ... | 2 | [illegible] |
| **Congrats! I can't wait to see you!!** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | [illegible] |

6 rows × 61 columns

In [94]:

```
type(toy_df["sms"])
```

Out[94]:

```
pandas.core.series.Series
```

```
Note that unlike other transformers we are passing a `Series` objec
t to `fit_transform`. For other transformers, you can define one tr
ansformer for more than one columns. But with `CountVectorizer` you
need to define separate `CountVectorizer` transformers for each tex
t column, if you have more than one text columns.
```

In [95]:
```
X_counts
```

Out[95]:
```
<6x61 sparse matrix of type '<class 'numpy.int64'>'
	with 71 stored elements in Compressed Sparse Row format>
```

### Why sparse matrices?

- Most words do not appear in a given document.
- We get massive computational savings if we only store the nonzero elements.
- There is a bit of overhead, because we also need to store the locations:
  - e.g. "location (3,27): 1".
- However, if the fraction of nonzero is small, this is a huge win.

In [96]:
```
print("The total number of elements: ", np.prod(X_counts.shape))
print("The number of non-zero elements: ", X_counts.nnz)
print(
    "Proportion of non-zero elements: %0.4f" % (X_counts.nnz / np.prod(
)
print(
    "The value at cell 3,%d is: %d"
    % (vec.vocabulary_["jackpot"], X_counts[3, vec.vocabulary_["jackpot
)
```

```
The total number of elements:  366
The number of non-zero elements:  71
Proportion of non-zero elements: 0.1940
The value at cell 3,27 is: 1
```

---

Question for you

- What would happen if you apply `StandardScaler` on sparse data?

---

### `OneHotEncoder` and sparse features

- By default, `OneHotEncoder` also creates sparse features.
- You could set `sparse=False` to get a regular `numpy` array.
- If there are a huge number of categories, it may be beneficial to keep them sparse.
- For smaller number of categories, it doesn't matter much.

### Important hyperparameters of `CountVectorizer`

- `binary`
  - whether to use absence/presence feature values or counts
- `max_features`
  - only consider top `max_features` ordered by frequency in the corpus
- `max_df`
  - ignore features which occur in more than `max_df` documents
- `min_df`
  - ignore features which occur in less than `min_df` documents
- `ngram_range`
  - consider word sequences in the given range

Let's look at all features, i.e., words (along with their frequencies).

In [97]:

```
vec = CountVectorizer()
X_counts = vec.fit_transform(toy_df["sms"])
bow_df = pd.DataFrame(
    X_counts.toarray(), columns=vec.get_feature_names_out(), index=toy_
)
bow_df
```

Out[97]:

| sms | 08002986030 | 100000 | 11 | 900 | always | are | around | as | been | call | ... | update | urgen |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| URGENT!! As a valued network customer you have been selected to receive a £900 prize reward! | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | ... | 0 | |
| Lol you are always so convincing. | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | ... | 0 | |
| Nah I don't think he goes to usf, he lives around here though | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | ... | 0 | |
| URGENT! You have won a 1 week FREE membership in our £100000 prize Jackpot! | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | |
| Had your mobile 11 months or more? U R entitled to Update to the latest colour mobiles with camera for Free! Call The Mobile Update Co FREE on 08002986030 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | ... | 2 | |
| Congrats! I can't wait to see you!! | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | |

6 rows × 61 columns

When we use `binary=True` , the representation uses presence/absence of words instead of word counts.

In [98]:
```
vec_binary = CountVectorizer(binary=True)
X_counts = vec_binary.fit_transform(toy_df["sms"])
bow_df = pd.DataFrame(
    X_counts.toarray(), columns=vec_binary.get_feature_names_out(), ind
)
bow_df
```

Out[98]:

| sms | 08002986030 | 100000 | 11 | 900 | always | are | around | as | been | call | ... | update | urgen |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| URGENT!! As a valued network customer you have been selected to receive a £900 prize reward! | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | ... | 0 | |
| Lol you are always so convincing. | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | ... | 0 | |
| Nah I don't think he goes to usf, he lives around here though | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | ... | 0 | |
| URGENT! You have won a 1 week FREE membership in our £100000 prize Jackpot! | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | |
| Had your mobile 11 months or more? U R entitled to Update to the latest colour mobiles with camera for Free! Call The Mobile Update Co FREE on 08002986030 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | ... | 1 | |
| Congrats! I can't wait to see you!! | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | |

6 rows × 61 columns

We can control the size of X (the number of features) using `max_features`.

In [99]:
```
vec8 = CountVectorizer(max_features=8)
X_counts = vec8.fit_transform(toy_df["sms"])
bow_df = pd.DataFrame(
    X_counts.toarray(), columns=vec8.get_feature_names_out(), index=toy
)
bow_df
```

Out[99]:

| sms | free | have | mobile | the | to | update | urgent | you |
|---|---|---|---|---|---|---|---|---|
| **URGENT!! As a valued network customer you have been selected to receive a £900 prize reward!** | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| **Lol you are always so convincing.** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| **Nah I don't think he goes to usf, he lives around here though** | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| **URGENT! You have won a 1 week FREE membership in our £100000 prize Jackpot!** | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 |
| **Had your mobile 11 months or more? U R entitled to Update to the latest colour mobiles with camera for Free! Call The Mobile Update Co FREE on 08002986030** | 2 | 0 | 2 | 2 | 2 | 2 | 0 | 0 |
| **Congrats! I can't wait to see you!!** | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |

Notice that `vec8` and `vec8_binary` have different vocabularies, which is kind of unexpected behaviour and doesn't match the documentation of `scikit-learn`.

[Here (https://github.com/scikit-learn/scikit-learn/blob/master/sklearn/feature_extraction/text.py#L1206-L1225)](https://github.com/scikit-learn/scikit-learn/blob/master/sklearn/feature_extraction/text.py#L1206-L1225) is the code for `binary=True` condition in `scikit-learn`. As we can see, the binarization is done before limiting the features to `max_features`, and so now we are actually looking at the document counts (in how many documents it occurs) rather than term count. This is not explained anywhere in the documentation.

The ties in counts between different words makes it even more confusing. I don't think it'll have a big impact on the results but this is good to know! Remember that `scikit-learn` developers are also humans who are prone to make mistakes. So it's always a good habit to question whatever tools we use every now and then.

In [ ]:
```
vec8 = CountVectorizer(max_features=8)
X_counts = vec8.fit_transform(toy_df["sms"])
pd.DataFrame(
    data=X_counts.sum(axis=0).tolist()[0],
    index=vec8.get_feature_names_out(),
    columns=["counts"],
).sort_values("counts", ascending=False)
```

In [ ]:
```
vec8_binary = CountVectorizer(binary=True, max_features=8)
X_counts = vec8_binary.fit_transform(toy_df["sms"])
pd.DataFrame(
    data=X_counts.sum(axis=0).tolist()[0],
    index=vec8_binary.get_feature_names_out(),
    columns=["counts"],
).sort_values("counts", ascending=False)
```

### Preprocessing

- Note that `CountVectorizer` is carrying out some preprocessing when used with default argument values, such as:
    - Converting words to lowercase ( `lowercase=True` )
    - getting rid of punctuation and special characters ( `token_pattern ='(?u)\\b\\w\\w+\\b'` )

In [100]:
```
pipe = make_pipeline(CountVectorizer(), SVC())
```

In [101]:
```
pipe.fit(toy_df["sms"], toy_df["target"])
```

Out[101]:
```
Pipeline(steps=[('countvectorizer', CountVectorizer()), ('svc', SVC())])
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**
**On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

In [102]:
```
pipe.predict(toy_df["sms"])
```

Out[102]:
```
array(['spam', 'non spam', 'non spam', 'spam', 'spam', 'non spam'],
      dtype=object)
```

### Is this a realistic representation of text data?

- Of course this is not a great representation of language
    - We are throwing out everything we know about language and losing a lot of information.
    - It assumes that there is no syntax and compositional meaning in language.
- But it works surprisingly well for many tasks.
- We will learn more expressive representations in the coming weeks.

## ❓❓ Questions for you

**`CountVectorizer` : True or False**

1. As you increase the value for `max_features` hyperparameter of `CountVectorizer` the training score is likely to go up.
2. Suppose you are encoding text data using `CountVectorizer` . If you encounter a word in the validation or the test split that's not available in the training data, we'll get an error.
3. `max_df` hyperparameter of `CountVectorizer` can be used to get rid of most frequently occurring words from the dictionary.
4. In the code below, inside `cross_validate` , each fold might have slightly different number of features (columns) in the fold.

```
pipe = (CountVectorizer(), SVC())
cross_validate(pipe, X_train, y_train)
```

**Identify column transformations**

Consider the restaurant data from the survey you did a few weeks ago.

In [ ]:
```
restaurant_data = pd.read_csv("../data/cleaned_restaurant_data.csv")
restaurant_data.head(10)
```

What all feature transformations you would apply on this dataset?

# What did we learn today?

- Motivation to use `ColumnTransformer`
- `ColumnTransformer` syntax
- Defining transformers with multiple transformations
- How to visualize transformed features in a dataframe
- More on ordinal features
- Different arguments `OneHotEncoder`
  - `handle_unknow="ignore"`
  - `if_binary`
- Dealing with text features

- Bag of words representation: `CountVectorizer`